Multi-State Residential Transaction Estimates of Solar Photovoltaic System Premiums

Authors:

Ben Hoen

Sandra Adomatis[1], SRA,

Thomas Jackson[2], MAI, CRE,

Joshua Graff-Zivin[3]

Mark Thayer[4]

Geoffrey T. Klise[5]

Ryan Wiser

[1] Adomatis Appraisal Services, [2] Real Property Analytics, Inc, [3] University of California at San Diego, [4] San Diego State University, [5] Sandia National Laboratories

Energy Analysis and Environmental Impacts Division
Lawrence Berkeley National Laboratory

This is the pre-print version of the following article:

Hoen, B., Adomatis, S., Jackson, T., Graff-Zivin, J., Thayer, M., Klise, G. T. and Wiser, R. "Multi-State Residential Transaction Estimates of Solar Photovoltaic System Premiums." Renewable Energy Focus, 19-20, 2017, 90-103.
https://doi.org/10.1016/j.ref.2017.05.006

June 2017

This work was supported by the Office of Energy Efficiency and Renewable Energy (Solar Energy Technologies Office) of the U.S. Department of Energy (DOE) SunShot Initiative under Lawrence Berkeley National Laboratory Contract No. DE-AC02-05CH11231.

Multi-State Residential Transaction Estimates of Solar Photovoltaic System Premiums

Ben Hoen[†] [a]
bhoen@lbl.gov

Sandra Adomatis, SRA [b]
adomatis@hotmail.com

Thomas Jackson, MAI, CRE [c]
tomjackson@real-analytics.com

Joshua Graff-Zivin [d]
jgraffzivin@ucsd.edu

Mark Thayer [e]
mthayer@mail.sdsu.edu

Geoffrey T. Klise [f]
gklise@sandia.gov

Ryan Wiser [a]
rhwiser@lbl.gov

[a] Lawrence Berkeley National Laboratory, 1 Cyclotron Road, MS 90R4000, Berkeley, CA 94720-8136
[b] Adomatis Appraisal Services, P.O. Box 511355, Punta Gorda, FL 33951
[c] Real Property Analytics, Inc. 4805 Spearman Drive, College Station, TX 77845-4412
[d] University of California at San Diego, 9500 Gilman Dr. 0519, La Jolla, CA 92093
[e] San Diego State University, 5500 Campanile Dr., San Diego, CA 92182-4485
[f] Sandia National Laboratories, PO Box 5800, MS 1137, Albuquerque, NM 87185

This is the pre-print version of the following article:

Hoen, B., Adomatis, S., Jackson, T., Graff-Zivin, J., Thayer, M., Klise, G. T. and Wiser, R. "Multi-State Residential Transaction Estimates of Solar Photovoltaic System Premiums." Renewable Energy Focus, 19-20, 2017, 90-103.
https://doi.org/10.1016/j.ref.2017.05.006

[†] Corresponding author: Phone: 845-758-1896; Email: bhoen@lbl.gov; Mailing address: 20 Sawmill Road, Milan, NY 12571.

Acknowledgements

We would especially like to thank the Office of Energy Efficiency and Renewable Energy (Solar Energy Technologies Office) of the U.S. Department of Energy (DOE) SunShot Initiative under Contract No. DE-AC02-05CH11231 for supporting this work. As well, we thank the many external reviewers for providing valuable comments on earlier drafts. Of course, any remaining errors or omissions are our own.

Abstract

As of the second quarter of 2016 more than 1.1 million solar photovoltaic (PV) homes exist in the US. Capturing the value these PV systems add to home sales is therefore important. Our study enhances the PV-home-valuation literature by analyzing 22,822 home sales, of which 3,951 have PV, and which span eight states during 2002–2013. We also, for the first time, compare premiums with contributory value estimates derived from the present value of saved energy costs (income approach) and, separately, the replacement cost of systems at the time of sale (cost approach) to examine market signals. We find home buyers are consistently willing to pay PV home premiums across various states, housing and PV markets, and home types; average premiums equate to approximately \$4/W or \$15,000 for an average-sized 3.6-kW PV system. We find that a replacement cost net of state and federal incentives is a better proxy for premiums than gross installed costs, and that the income approach is a good signal if it accounts for tiered volumetric retail rates. Other results include detailed premium analyses for PV home sub-populations.

Keywords: Solar, PV, Home Prices, Hedonic, Premium, Depreciation

Highlights

- 4,000 transactions of solar homes in eight states spanning 2002–2013 are analyzed
- Premiums are present across the data including sub-samples
- Premiums equate to ~ $4/W or $15,000 for an average-sized 3.6-kW PV system
- Premiums decrease dramatically as PV systems age 10 years, dropping almost 60%
- Net cost estimates seem to be generally consistent with market value premiums

Statement of Significance

As of the second quarter of 2016 more than 1.1 million solar photovoltaic (PV) homes exist in the US. Capturing the value these PV systems add to home sales is therefore important. Since 2013 virtually no new research has emerged on the subject of contributory value of PV on homes, despite that there have been a number of high profile news stories claiming that solar can adversely affect sales of homes.

Our study enhances the PV-home-valuation literature by analyzing the largest number of solar home sales to-date. We also, for the first time, compare hedonic model premiums with contributory value estimates derived from the present value of saved energy costs (income approach) and, separately, the replacement cost of systems at the time of sale (cost approach) to examine market signals.

We find home buyers are consistently willing to pay PV home premiums across various states, housing and PV markets, and home types. We find that a replacement cost net of state and federal incentives is a better proxy for premiums than gross installed costs, and that the income approach is a good signal if it accounts for tiered volumetric retail rates.

These results should provide strong evidence to the policy makers at HUD, Fannie Mae, Freddie Mac and other institutions, as well as the research and industry communities that premiums do exist for some PV homes, and that additional research is warranted in the area.

1. Introduction

As of the second half of 2016, solar photovoltaic (PV) energy systems have been installed on more than 1.1 million properties in the United States; more than 300,000 systems were installed in 2015 alone (SEIA & GTM, 2016). This growth is in part related to the dramatic decrease in installed PV costs over the last 10 years (Barbose et al., 2014) as well as the increase in financing options for property owners installing PV, such as leased PV systems and other zero-money-down purchase options (SEIA & GTM, 2016). The U.S. Department of Energy estimates that achieving its SunShot PV system price-reduction targets could result in 108 GW of residential rooftop PV installed by 2050—equivalent to 30 million American homes with PV (US DOE, 2012).[1]

As PV installations have proliferated, so has the number of transactions involving homes with PV (Adomatis and Hoen, 2016). Because of this, the real estate sales and valuation communities have evolved accordingly (Adomatis, 2014). For example, courses on the valuation and marketing of green features are available through the Appraisal Institute and the National Association of REALTORS®,[2] respectively. New policy documents have been issued by Fannie Mae (2016) and the Federal Housing Administration (HUD, 2016), which provide appraisers the tools and guidance for recognizing solar as a potentially valuable asset.

Despite the activity around valuing PV homes, little research documents the premiums for these homes. Farhar and Coburn (2008) first documented the apparent increase in values for 15 PV homes inside a San Diego subdivision. This was later corroborated by strong empirical evidence from greater San Diego and Sacramento (Dastrup et al., 2012) and from a dataset of approximately 1,900 California PV homes (Hoen et al., 2011; 2013a; 2013b); these studies employed hedonic pricing models to estimate premiums. Additionally, three appraiser-led studies using paired sales analysis of fewer than 45 homes found further evidence of premiums in Oregon (Watkins, 2011) the Denver metro area (Desmarais, 2013), and from six states in the US (Adomatis and Hoen, 2016). Because the evidence that PV homes garner a premium has focused on a relatively small number of California homes and a few in Colorado, Oregon and other states, there is need for further evidence of premiums outside of California and even inside California using large datasets. There is also a need to analyze transactions that occurred after the housing bubble ended in 2008, because most previous studies analyzed transactions that occurred during that bubble (Hoen et al., 2011; 2013a; 2013b).

In most local markets, few PV home sales occur, thus appraisers and other real estate professionals (real estate agents, lenders, underwriters, etc.) often cannot compare similar PV and non-PV home sales to derive a PV premium. Because of this, valuation professionals often use other methods to value PV systems, including the income and cost methods (Klise et al., 2013; Adomatis, 2014; FHA, 2015). Although some past studies have compared results from these methods to results derived from transaction analysis (Desmarais, 2013; Hoen et al., 2013a), they have not applied statistical analysis and thus cannot statistically quantify the comparisons. Such a statistical comparison would be a valuable contribution to the literature, especially using a more recent and broader group of transactions.

Other considerations are important as well. The gross installed costs (i.e., costs before state and federal incentives) of PV systems have declined steadily in recent years, while net costs (i.e., with incentives included) have remained fairly stable (Barbose et al., 2014). There also has been evidence that the new home market in California heavily discounted PV homes during the housing boom and bust (through

[1] Assuming the average PV system size of 3.6 kW found for all PV homes in this study.

[2] See, e.g., http://www.appraisalinstitute.org/education/education-resources/green-building-resources/ and http://www.greenresourcecouncil.org/.

2009) in comparison to the premiums garnered by existing home sellers (Hoen et al., 2011; 2013a).[3] Finally, previous literature suggests the need for more research on the market's depreciation of aging PV systems, especially for systems greater than 6 years old, which have not been well studied because of the immaturity of the PV market (Hoen et al., 2011; 2013a; 2013b).

In summary, the existing literature leaves open a number of questions, each of which the present research seeks to address. Table 1 shows these questions along with models and sample sets, which are discussed later.

Table 1: Summary of Research Questions, Models, and Sample Sets

Research Question	**Model Name**	**Sample Set(s)**
1. Are PV home premiums evident for a broader group of PV homes than has been studied previously both inside and outside of California and through 2013?	Base Model	All Data
2. Are PV home premiums outside of California similar to those within California?	Location Models	CA vs. Non-CA Homes
3. How do PV home premiums compare to contributory values estimated using the cost and income methods?	Various Models	All Data, or Subsets of Data, But Compare Results To Income and Cost Methods
4. How did the size of the premium change over the study period, as gross PV system prices decreased and during housing market swings?	Year of Sale Models	Subsets of Years in Sample Period (e.g., Pre-'08; 08-09, 10-11, Post 11)
5. Are premiums for new PV homes similar to existing PV home premiums?	Home Type Models	New vs. Existing Homes
6. How does the age of the PV system influence the size of the PV premium?	Age of PV System Models	Subsets of PV System Ages (e.g., < 2 years; 2-4; 5-6; 7-14 years)

This research focuses on only <u>host-owned</u> PV systems and therefore excludes third-party-owned systems, which, we recommend, should be included in future research because they make up a large percentage of the most recent PV installations.

The remainder of this report is organized as follows: Section 2 discusses our methodological approach, Section 3 details the data used for the analysis, Section 4 presents the results, and Section 5 offers conclusions and directions for future work.

[3] These discounts, it was assumed, were offset by decreased marketing times (i.e., "sales velocity") for these homes, a priority for home builders as the market for new homes slowed and inventories increased (Dakin et al., 2008; Farhar and Coburn, 2008; SunPower, 2008).

2. Methodological Approach

To examine the questions above, this research relies on a hedonic pricing model—the "Base Model"—against which a series of other models are compared. Those other models use a subset of the data (e.g., new or existing homes), an interaction term(s) (e.g., age of the PV system), or other variants to examine the various research questions and test the overall robustness of the results.

The basic theory behind the hedonic pricing model starts with the concept that a house can be thought of as a bundle of characteristics. When a price is agreed upon between a buyer and seller, there is an implicit understanding that those characteristics have value. When data from a number of sales are available, the average marginal contribution to the sales price of each characteristic can be estimated with a hedonic regression model (Rosen, 1974; Freeman, 1979; Sirmans et al., 2005). This relationship takes the basic form:

Sales price = f (home and site, neighborhood, and market characteristics)

"Home and site characteristics" might include, but are not limited to, the number of square feet of living area and the presence of a PV system. "Neighborhood" characteristics might include such variables as the crime rate and the distance to a central business district. Finally, "market characteristics" might include, but are not limited to, temporal effects such as housing market inflation/deflation.

2.1 Base Model

The "Base Model" to which other models are compared uses a relatively simple set of home and site characteristics: size of the home (i.e., square feet of living area); age of the home at the time of sale (in years); age of the home squared (in years); size of the parcel (in acres) up to 1 acre; and any additional acres more than 1 (in acres).[4] It also includes the presence and size of the PV systems. To control for neighborhood, we include a census block group fixed effect, which, in all cases, includes at least one PV home and one non-PV home. Finally, market characteristics are accounted for by including a dummy variable for the quarter and year (e.g., 2013 Q2, 2009 Q1, etc.) in which the sale occurred. This model form was chosen for its relative parsimony, its high adjusted R^2, and its transparency.[5] It is estimated as follows:

$$\ln(\mathrm{P}_{\mathrm{itk}}) = \alpha + \beta_1\left(\mathrm{T_i}\right) + \beta_2\left(\mathrm{K_i}\right) + \sum_{\mathrm{a}} \beta_3\left(\mathrm{X_i}\right) + \beta_4\left(\mathrm{PV_i} \cdot \mathrm{SIZE_i}\right) + \varepsilon_{\mathrm{itk}} \tag{1}$$

where

P_{itk} represents the sale price for transaction *i*, in quarter *t*, in block group *k*,

α is the constant or intercept across the full sample,

---

[4] Acres is entered into the model as a spline function using two variables, up to 1 acre (*acreslt1*) and any additional acres above 1 (*acresgt1*), to capture the different values of up to the first and additional acres of parcels in the sample. Therefore *acreslt1 = acres* if *acres* ≤ 1 and 1 otherwise, while *acresgt1 = acres*-1 if *acres* > 1 and 0 otherwise. Additionally, square feet and age squared are entered into the model in 1,000s to allow for easier interpretation of the coefficients.

[5] Model choice for this work was based on extensive robustness model exploration in previous analysis (Hoen et al., 2011; 2013a; 2013b). Other models were explored but are not presented here. They include adding other home and site parameters such as number of bathrooms, condition of the home, and if a pool is present, all of which further limited the dataset but did not substantively affect the results. Similarly, instead of using a fixed effect for sale year and quarter, interacting sale year and, separately, sale quarter, with a geographic variable, such as county, to control for geographic variation in market inflation/deflation was explored with no change to the results.

T_i is the quarter t in which transaction i occurred,

K_i is the census block group k in which transaction i occurred,

X_i is a vector of a home and site characteristics for transaction i,

PV_i is a fixed-effect variable indicating a PV system is installed on the home in transaction i,

$SIZE_i$ is a continuous variable for the size (in kW) of the PV system installed on the home prior to transaction i,[6]

β_1 is a parameter estimate for the quarter in which transaction i occurred,

β_2 is a parameter estimate for the census block group in which transaction i occurred,

β_3 is a vector of parameter estimates for home and site characteristics a,

β_4 is a parameter estimate for the change in sale price for each kilowatt added to a PV system, and

ε_{itk} is a random disturbance term for transaction i, in quarter t, in block group k.

The parameter estimate of primary interest in this model is β_4, which represents approximately the marginal percentage change in sale price over the average sale price of the comparable set of non-PV homes within the same census block group, with the addition of each kilowatt of PV.[7] If differences in selling prices exist between PV and non-PV homes, we would expect the coefficient to be positive and statistically significant.

This model allows an examination of many of the research questions (Table 1) depending on the dataset that is used. If the full dataset is used, the first question can be answered. If a subset of the dataset is used, many of the other questions can be answered. For example, if homes within and outside California are used, the second question can be explored. Similarly, if the data are restricted to particular subsets of the study period (e.g., 2002–2007, 2008–2009, 2010–2011, or 2012–2013), the fourth research question could be examined. To explore if new or existing homes had similar premiums (the fifth question), the data could be restricted to those subsets. Finally, if only PV systems of particular ages were used, the sixth question could be answered. Therefore, almost all of the research questions can be answered using subsets of the data, leaving only the third question, which can use either the full dataset or subsets of the data but also requires calculations of comparison valuation estimates using the cost or income method.[8]

2.2 Robustness Models

We also explore the robustness of our results with two alternative model specifications.

2.2.1 PV Only Model

It has been well documented that PV homes often have a suite of additional energy-efficiency (EE) features (CPUC, 2010; Hee et al., 2013; Langheim et al., 2014). Further, it has been theorized that PV home owners, who have the financial resources to install a PV system, might also make other (non-EE)

---

[6] All references to the size of PV systems in this paper, unless otherwise noted, are reported in terms of direct-current watts (or kilowatts) under standard test conditions. A discussion of this convention is offered in Appendix A of Barbose et al. (2014).

[7] To be exact, the conversion to percent is actually $EXP(\beta_4)-1$, but the differences are often *de minimis*.

[8] Although the preferred method is to estimate a separate model using a subset of the data, which allows all of the controlling parameters to take different values for each subset, we also explored estimating models with a categorical variable for each of the subsets interacted with either the variable of interest only <u>or</u> both the variable of interest and the other controlling parameters, with no substantive change in the results.

upgrades, such as a new kitchen or bathroom, or may alternatively replace their roof contemporaneously with PV system installation. Therefore, the premium estimated from Equation (1) could also include effects of EE and other features and therefore overestimate the effect related to PV alone.

To test this, PV homes are compared to other PV homes based on system size. While the Base Model estimates a difference in sales prices between PV and non-PV homes, all else being equal, the PV Only Model compares the difference between PV homes and PV homes based on differences in their PV system size, all else being equal. Assuming all PV homes have the same frequency of EE and other features among them, an effect free of those influences can be estimated and then compared to the results in Equation (1).[9]

One complication of this model concerns possible collinearities of the block group fixed effects and PV when a single or small number of PV homes exist within a single block group. While in the Base Model the use of the block group fixed effect is appropriate, because each contains at least one PV and one non-PV home, in the PV Only Model collinearities might exist for block groups with only one or a few PV homes, or those that might have only similarly sized PV systems. In those block groups, the fixed effect might absorb the contributory effect of the PV variable. Therefore, this model uses the county as the fixed effect and is restricted to counties that have two or more PV homes, to allow more heterogeneity between the PV homes within the fixed effect delineation and therefore less collinearity between them and the PV variable; otherwise the model is identical to Equation (1).[10]

2.2.2 Repeat PV Home Model

A common concern with a hedonic model, such as the Base Model, is that a suite of home and site characteristics are not controlled for, which could be driving the results. These omitted variables could include any manner of home features, such as granite countertops, a newly renovated basement, and Jacuzzi, as well as neighborhood features, such as location on a cul-de-sac, a scenic vista, or location next to a major road. These variables could be present for PV and non-PV homes. Although the assumption is that these unobserved features are randomly distributed among PV and non-PV homes, and therefore are not correlated with the presence of PV, this might not be the case. This can be tested using the Repeat PV Home Model.

The Base Model estimates a difference in sales prices between PV and non-PV homes all else being equal, but the Repeat PV Home Model compares sales prices of homes before they had PV installed to prices of the same homes after they had PV installed. Because many of the characteristics controlled for in the Base Model are held constant in the Repeat PV Home Model, such as block group and size of the home and parcel, they do not need to be controlled for.[11] Therefore, the following greatly simplified model can be estimated:

---

[9] It is at least conceivable that EE and other features are correlated with PV system size, with a larger PV system correlated with more EE and other features. We expect, however, that this would likely be more correlated with the size of the home, which is controlled for in this and the Base Model.

[10] Although not shown here, using county fixed effects in the Base Model in place of block group fixed effects has no apparent effect on the premium estimate, and therefore this PV Only Model can be compared directly to the Base Model results. Also, this model assumes a tradeoff between being able to compare PV homes to PV homes, and therefore controlling for the unobservables associated with PV, versus controlling for the unobservables associated with the localized neighborhood effects that the block group fixed effect controls for.

[11] Ideally we would have information on the size of the home as of the first sale and the second sale, but we only have information from the most recent assessment and therefore can only assume that it has not changed between sales. If it has changed, however, it would have likely increased the home's value, thus the second sale would include the increase in related value. If this were the case, the PV premium would capture this increase. Our results do not exhibit this increase, so it is assumed that the Repeat PV Home Model results are free of this influence.

$$\ln(P_{itk}) = \alpha + \beta_1 (T_i) + \sum_a \beta_2 (X_i) + \beta_3 (PV_i \cdot SIZE_i) + \varepsilon_{itk} \qquad (2)$$

where

X_i is a vector of age of the home and age squared for transaction *i*,

β_2 is a vector of parameter estimates for age and age squared,

β_3 is a parameter estimate for the change in sale price for each additional kilowatt added to a PV system, and all other variables are as defined in Equation (1).

3. Data Preparation and Summary

This section describes the underlying data used for this analysis—including PV home and non-PV home data, cost estimates, and income estimates—followed by a data summary.

3.1 PV and Non-PV Home Data

For the Tracking the Sun (TTS) report series (e.g., Barbose et al., 2013), Lawrence Berkeley National Laboratory was provided a set of approximately 150,000 host-owned (i.e., not third-party-owned) PV home addresses by various state and utility incentive providers, along with information on PV system size, date the incentive was applied for, date the system was put into service, and the average tilt and azimuth of the PV system, where available.[12] These data span the years 2002–2013 and stretch across eight states: California, Connecticut, Florida, Massachusetts, Maryland, North Carolina, New York, and Pennsylvania.

These PV home addresses were matched to addresses maintained by CoreLogic,[13] which CoreLogic aggregates from county-level assessment and deed recorder offices. Once the addresses were matched, CoreLogic provided, when available, real estate information on each of the PV homes as well as similar information on approximately 200,000 non-PV homes located in the same (census) block group as the PV homes. The data for both of these sets of homes included, but were not limited to:

- address (e.g., street, street number, city, state, and zip+4 code);
- most recent and previous (if applicable) sale date and amount;
- home characteristics (e.g., acres, square feet of living area, bathrooms, pool, and year built);
- assessed value of land and improvements;
- parcel land use (e.g., commercial, residential);
- structure type (e.g., single-family residence, condominium, duplex); and,
- x/y coordinates.

These data were cleaned to ensure all data were populated and appropriately valued.[14] Using these data, along with the PV incentive provider data, we determined if a home sold after a PV system was installed, significantly reducing the usable sample because the majority of PV homes have not yet sold. We also culled a subset of these data for which previous sale information was available and for which a PV system had not yet been installed as of this previous sale. These "repeat sales" were used in the Repeat PV Home Model described in Section 2.2.2 .

Ideally, for each PV home transaction, we would have a set of identical (i.e., all else being equal) non-PV home transactions for comparison. This theory underlies the comparable-sales method used by appraisers and other valuation professionals (Adomatis, 2014), where comparable homes are chosen that are as similar as possible, and then adjustments are made to account for the observable differences.

[12] For a full discussion of how these data are obtained, cleaned, and prepared, see Barbose et al. (2013).

[13] More information about this product can be obtained from http://www.corelogic.com/.

[14] Because the CoreLogic data sometimes are missing or miscoded, the cleaning and preparation of these data were extensive and therefore not detailed here, but the process included the following screens: sale price greater than $165,000 and less than $900,000, size of the home between 1,000 and 5,000 square feet, sale price per square foot between $8 and $800, sale year after 2001, and size of the parcel between 0.05 and 10 acres.

To emulate the comparable-sales method, we employed the Coarsened Exact Matching (CEM) process (King et al., 2010), which finds a matched sample of PV and non-PV homes that are statistically equal on their covariates.[15] The covariates include being within the same block group, selling in the same year, and having similar values for size of the home, age of the home, size of the parcel, and ratio of assessed value of land to total assessed value.[16] This procedure results in a reduced sample of homes to analyze, but biases related to the selection of PV and non-PV homes are minimized.[17] The unmatched dataset has 173,982 non-PV homes and 5,373 PV homes, while the matched dataset—the one used for the analysis—has 18,871 non-PV homes and 3,951 PV homes. Various models, as described above, use subsets of the PV homes and therefore need matching non-PV homes. For most of the subsets this is straightforward, because we divide the PV and non-PV homes along the same lines used for the CEM matching, such as whether the homes are located in California or the rest of the United States, or if they are newly built or existing homes. When comparing premiums among PV systems of different ages, however, there is not an intuitive division for the non-PV homes, because age of the PV system was not used for matching. Therefore, for these models, the CEM process was employed again for each set of PV homes. The resulting matched non-PV homes were not necessarily mutually exclusive between the sets of PV homes, but most importantly each block group contained at least one PV home and one non-PV home.

3.2 Cost Estimates

In this analysis, as in previous studies (Hoen et al., 2011; 2013a; 2013b), we compare the market premiums we find using our Base Model and alternative models to cost and income contributory-value estimates to illuminate how the market might be reacting to various signals. A cost estimate refers to the cost to replace an asset with a new equivalent. Appraisal theory posits that cost estimates are likely important price signals in the marketplace, and market values normally should not exceed the replacement cost of an asset. This might mean, for example, that a buyer of a PV system already installed on a home is not willing to pay more for it than the cost of a new system (i.e., its replacement cost).

For this analysis, we prepared two sets of cost estimates: gross costs and net costs. Both estimates were prepared for each home at the time of sale, based on the following characteristics: county in which the home is located, year of the sale, and size of the system. The detailed preparation of these estimates is described in (Hoen et al., 2015). In our context, "net" implies a cost after federal and state tax incentives and state rebates are factored in, while "gross" estimates do not factor these incentives in.[18] We distinguish between the two because, for most homeowners, the perceived out-of-pocket cost is the net cost, after incentives, and therefore the net cost might be a better market signal than the gross cost.

---

[15] The procedure used, as described in the referenced paper, is CEM in Stata, available at: http://ideas.repec.org/c/boc/bocode/s457127.html. Because this matching process excludes non-PV homes that are without a statistically similar PV match (and vice versa), a large percentage of homes (approximately 90% of non-PV and 33% of PV) are *not* included in the resulting dataset. Pre-matching Multivariate Distance (0.95) compares favorably to post-matching Distance (0.82).

[16] The assessed value of land to total value ratio is expected to capture the unexplained within-block group locational variation that often is present, for example, due to being on a quiet road, abutting a park, or being on the waterfront. Assessed values, it is assumed, are consistently applied within the block group.

[17] Although the preferred model is one with a matched dataset, the Base Model was also estimated using the unmatched dataset, which results in a slightly higher estimated premium. We attribute this change to the heterogeneity of the unmatched PV and non-PV homes and the fact that the unmatched non-PV homes have lower-valued unobserved characteristics.

[18] Other incentives exist, such as state renewable energy credits, feed-in tariffs, and performance-based incentives, but these are rare throughout the analysis dataset and therefore are not considered. Understanding how to value them appropriately should be the subject of future research, however, because their value can be significant in certain circumstances.

Additionally, taking advantage of tax incentives is somewhat dependent on a homeowner's tax obligations. For example, the federal incentive for PV comes in the form of a reduced federal tax obligation (formally known as the Internal Revenue Code Section 25D: Residential Energy Efficient Property Credit). If a homeowner expects to pay very little in taxes (e.g., because they have a mortgage and very little taxable income), then the federal tax incentive might not be realized immediately (it can be carried over year to year). A similar scenario exists if state tax incentives are present. More generally, incentive availability changes with time, so home buyers may have uncertainty about the availability and value of incentives. Because of these different scenarios, it is not immediately clear if the market would fully capitalize the incentives calculated as part of the net cost, thus net cost can serve as the low cost estimate for our purposes. Similarly, we expect that buyers would not be willing to pay more than the gross cost, so this serves as the high cost estimate.

Finally, in previous analyses, we prepared cost estimates depreciated using a straight-line 20-year depreciation schedule, assuming this would be roughly equivalent to the usable life of a PV system (Hoen et al., 2011; 2013a; 2013b). For the present analysis we use, instead, the un-depreciated amount. In doing so, we do not presuppose how the market depreciates PV systems and/or the replacement costs of those systems; rather, we allow the market to dictate how best to depreciate their values, if at all. This is the customary approach of appraisers (Adomatis, 2014).

3.3 Income Estimates Using the PV Value Algorithm

As with cost estimates, appraisal theory posits that income estimates—a discounted stream of income derived from an asset over time, such as rent—are likely important price signals in the marketplace. For example, an apartment seller might not be willing to sell a property for significantly less than the present value of rent (minus costs) it receives for that property. Similarly, the buyer and seller of a home with a PV system might use the discounted value of the system's energy cost savings as a key factor in determining any PV premium.

For each of the PV homes in our sample, we prepared data to estimate the present value of energy produced by the PV system (income estimates) using the size and age of the system, the zip code of the home, and the estimated tilt and azimuth of the system.[19] These inputs were fed through the PV Value algorithm (Johnson and Klise, 2012; Klise et al., 2013) to produce present-value estimates for utility bill savings for a similarly sized system as of the time of sale.[20] Detailed descriptions of the income estimation procedure are contained in (Hoen et al., 2015) and elsewhere (Johnson and Klise, 2012; Appendix A in Hoen et al., 2013b; Klise et al., 2013). The algorithm uses an average zip-code-level electricity rate as the default, which we also used. Therefore, tiered rates, which are prevalent in California, are not considered in this calculation because we lacked house-specific information about what tiers are typically avoided based on the size of the PV system and energy demand profile. We return to this issue briefly in our conclusion, where we compare the income estimates with results from the model estimation.

3.4 Data Summary

The final dataset includes 22,822 transactions, consisting of matched PV (n = 3,951) and non-PV (n = 18,871) homes. This full matched dataset is composed of transactions occurring across eight states (Table

[19] Because tilt and azimuth were not available for all PV systems (the data were not provided during the TTS data-collection effort), they were estimated via a cascading approach, based on systems with those data in the same census block group if available, then, if not available, census tract or, finally, county when needed.

[20] The estimation procedure produces a set of low, average, and high estimates of the present value of the expected energy output, based on a risk premium of 200, 100, and 50 basis points on top of the base discount rate, respectively. Only the average value was used for this analysis.

2) from 2002 to 2013 (Table 3), with the vast majority in California. All PV systems in this dataset are homeowner (host) owned as opposed to third-party owned (leased or under a power-purchase agreement).

Table 2: Frequency Summary of PV and Non-PV Homes by State

State	Non-PV Homes	PV Homes	Total
CA	18,207	3,828	22,035
FL	317	25	342
Mid-Atlantic Region: MD, NC, PA	288	77	365
Northeast Region: CT, MA, NY	59	21	80
Total	**18,871**	**3,951**	**22,822**

Table 3: Frequency Summary of PV and Non-PV Homes by Sale Year

Sale Year	Non-PV Homes	PV Homes	Total
2002	107	18	125
2003	196	31	227
2004	238	53	291
2005	197	56	253
2006	348	64	412
2007	818	242	1,060
2008	1,251	453	1,704
2009	1,762	429	2,191
2010	2,751	504	3,255
2011	3,341	642	3,983
2012	3,928	694	4,622
2013	3,934	765	4,699
Total	**18,871**	**3,951**	**22,822**

Summary statistics for the PV and non-PV homes are shown, respectively, in Table 4 and Table 5. The mean sale price (*sp*) of the PV homes in the sample is $473,373 and ranges from a minimum of $165,500 to a maximum of $899,500. The average PV home in the sample has 2,334 square feet of living area (*sfla*), is located on a parcel of 0.45 acres (*acres*), and was 17 years old (*age*) when it sold in 2010 (*sy*).[21] It has a 3.6-kW PV system (*size*), which was installed 2.7 years before the home was sold (*pvage*). The gross installed cost for a similarly sized PV system in the same county at the time of sale was $6.90/W (*grosscost*), while the net cost (after incentives) was $4.14/W (*netcost*). The present value of the stream of energy produced by the PV system, as calculated by the PV Value algorithm, is $2.93/W (*income*). PV

[21] Negative values for the minimum age of a home (e.g., -2) apply to newly built homes in the sample and occur when the sale date is prior to the date of home completion, as might occur when a home is purchased on spec. Similarly, for PV system age, a negative minimum value occurs when the completion date of the PV system occurred before the home sale date, which happens sometimes for new homes. Additionally, although acres is shown in the tables, it is entered in the model as a spline function of up to 1 acre and any additional acres above 1 (see Section 2.1). Finally, age of the home squared is not shown in the tables.

systems in the sample range in size from 0.1 kW to 14.9 kW, with a median of 2.8 kW (*size*). The age of the PV systems at the time of sale ranges from new to more than 13 years, with a median of 2.2 years (*pvage*). For the 18,871 non-PV homes, we find a mean sale price of $456,378, which is $16,995 lower than that of the matching PV homes. The average non-PV home is slightly smaller than the average PV home (2,319 square feet), occupies a smaller parcel (0.41 acres), and is equivalent in age. The dataset contains 7,480 newly built homes and 15,342 existing homes, of which 1,444 and 2,507, respectively, are PV homes.

Table 4: Summary Statistics for All PV Homes

variable	description	N	mean	sd	min	median	max
sy	year of sale	3951	2010	2	2002	2011	2013
syq	year and quarter of sale (yyyyq)	3951	20103	23	20021	20111	20134
sp	price of sale (dollars)	3951	$ 473,373	$ 196,451	$ 165,500	$ 433,000	$ 899,500
lnsp	natural log of sale price	3951	12.98	0.43	12.02	12.98	13.71
sfla	living area (square feet)	3951	2,334	702	1,006	2,244	4,981
sfla1000	living area (in 1000s of square feet)	3951	2.3	0.7	1.0	2.2	5.0
acres	size of parcel (in acres)	3951	0.45	0.95	0.05	0.18	9.99
age	age of the home at time of sale (years)	3951	17	21	(2)	7	100
agesq1000	age of the home squared (in 1000s of years)	3951	0.7	1.3	0	0.0	10.0
pv	if the home has a PV system (1 if yes)	3951	1	-	1	1	1
size	size of the PV system (kilowatts)	3951	3.6	2.0	0.1	2.8	14.9
pvage	age of the PV system at time of sale (years)	3951	2.7	2.9	(0.5)	2.2	13.4
income	average PV Value estimate ($/watt)	3951	$ 2.93	$ 0.57	$ 1.18	$ 2.92	$ 4.98
netcost	net cost estimate ($/watt)	3951	$ 4.14	$ 0.93	$ 1.07	$ 4.04	$ 7.95
grosscost	gross cost estimate ($/watt)	3951	$ 6.90	$ 1.50	$ 3.15	$ 6.92	$ 11.83

Table 5: Summary Statistics for All Non-PV Homes

variable	description	N	mean	sd	min	median	max
sy	year of sale	18871	2010	2	2002	2011	2013
syq	year and quarter of sale	18871	20103	23	20021	20112	20134
sp	price of sale (dollars)	18871	$ 456,378	$ 197,004	$ 165,500	$ 413,000	$ 899,500
lnsp	natural log of sale price	18871	12.94	0.44	12.02	12.93	13.71
sfla	living area (square feet)	18871	2,319	714	1,001	2,200	4,990
sfla1000	living area (in 1000s of square feet)	18871	2.3	0.7	1.0	2.2	5.0
acres	size of parcel (in acres)	18871	0.41	0.86	0.05	0.18	9.8
age	age of the home at time of sale (years)	18871	17	21	(2)	8	100
agesq1000	age of the home squared (in 1000s of years)	18871	0.7	1.3	0	0.1	10.0
pv	if the home has a PV system (1 if yes)	18871	0	0	0	0	0

4. Results

This section presents results, starting with the Base Model, which addresses the first research question: Are PV home premiums evident for a broader group of PV homes than has been studied previously? This is followed by results for the various other models, which explore the remainder of the research questions (Table 1 shows the full set of questions), and the two robustness models.

4.1 Base Model Results

The Base Model estimates, over the entire dataset, the marginal return to each kilowatt of PV installed on a home as defined in Equation (1). The model is summarized in Table 6.[22] Overall the model performs well, with an adjusted R^2 of 0.92.

Table 6: Base Model Results Summary

Total *n*	22,822
PV *n*	3,951
Non-PV *n*	18,871
Adjusted R^2	0.92
Dependent Variable	lnsp
Block Group Fixed Effects *n*	1,830

The full set of results is shown in **Error! Reference source not found.**. The controlling variables that account for size (*sfla1000*) and age of the home (*age*, *agesq1000*) and size of the parcel (*lt1acres*, for each acre up to 1, and *gt1acres*, for each acre over 1) are all highly statistically significant (i.e., p-value < 0.001). The model indicates that, in our sample, each additional 1,000 square feet adds approximately 21% to the selling price, while each acre up to 1 adds 39% and each additional acre beyond 1 adds 3%.[23] Each year a home ages initially takes approximately 0.7% off its value, but this annual value reduction declines with time, and homes over approximately 60 years in age appreciate in value as they age.[24] Using the fourth quarter of 2013 as the reference category, in our sample, prices start approximately 44% lower (Q1 2002) and then increase to approximately 20% higher (2005), before falling again to lows in early 2012 and then increasing to levels present in late 2013. This rise, fall, and eventual recovery are entirely consistent with the national trends in housing prices.[25] Combined, the various controlling characteristics are appropriately signed and leveled based on our expectations, giving us confidence that the model is acting appropriately and adequately capturing price differences across the sample.

---

[22] All models are estimated in Stata using *areg*, with block groups as the absorbed fixed effect and with robust standard errors.

[23] The exact percentage interpretation of coefficients in a semi-log model is as follows: exp(coefficient)-1, but the differences in this context are *de minimis*.

[24] Approximately 60 years is determined by dividing the age coefficient by the first derivative of the square term's (*agesq*) coefficient.

[25] As noted previously, we also explored interacting the year of sale with the county, to capture regional price trends, with no substantive change to the results.

Turning to the variable of interest, *pv*size*, the model estimates that, for each kilowatt of installed PV, sale prices increase by 0.91%, and this estimate is highly statistically significant (*p*-value < 0.001).[26] Accordingly, at the 95% confidence interval, average price increases are estimated to vary between approximately 0.78% and 1.05% per kilowatt, a relatively precise estimate. This sample of approximately 4,000 PV homes shows a clear premium for each kilowatt of PV installed above the sale prices of comparable non-PV homes.

By using the mean sale price (in dollars) for non-PV homes, we can convert this percentage estimate into dollars per watt.[27] Doing so leads to an estimated premium of $4.18/W, with a 95% confidence interval of +/- $0.62/W, which corresponds to a premium of approximately $15,000 for an average-sized system of 3.6 kW. From Table 4, we see that, for these PV homes, the mean gross cost estimate is $6.90/W (*sd* = $1.50/W), while the net cost estimate is $4.14/W (*sd* = $0.93/W), and the average PV Value (income) estimate is $2.93/W (*sd* = $0.57/W). Therefore, the premium in our sample is very similar in size and is not statistically different from the average net cost for a similarly sized system as of the time of sale. Further, it is not statistically different than the PV Value income estimate, but it is $1.25/W higher. It is statistically different and approximately $2.70/W lower than the gross cost estimate.

When considering the income estimate, the retail electricity rate used to calculate the savings is particularly important. The PV Value tool uses the average retail electricity rate as a default (for our sample that is $0.154/kWh), and this is what we used to calculate income estimates. However, tiered volumetric electricity rates based on the customer's consumption are normal for most residential PV customers in California (CPUC, 2013). If customers consume more than the average retail customer, then they will be moved into higher-priced tiers, and even a relatively small rate increase would result in a substantial increase in the income estimate. For example, if the rate increased by $0.05/kWh, it would increase the PV Value estimate from $2.93/W to almost $4/W, which is very similar to (and also not statistically different from) the premium estimate. Therefore, it seems possible that buyers and sellers might be using the electricity cost savings as an important price signal, but they are estimating those savings at a slightly higher rate than the tool's default average retail rate.

---

[26] The standard error for the Base Model of 0.0007 is 35% of the standard error found in the previous analysis of California PV homes of 0.0018 (Hoen et al. 2011; 2013a), indicating the increased precision of this estimate.

[27] The formula for doing so is: $/W premium = ((exp (*pv*size* coefficient)-1)* *mean sale price in dollars for non-PV homes*)/1,000.

Table 7: Base Model Results

Variable	Coefficient	Standard Error	*t* Statistic	*p*-value	- 95% CI	+ 95% CI
intercept	12.498	0.016	758.00	0.000	12.465	12.530
pv*size	0.0091	0.0007	13.12	0.000	0.0078	0.0105
sfla1000	0.213	0.004	51.70	0.000	0.205	0.221
lt1acre	0.386	0.028	13.73	0.000	0.331	0.441
gt1acre	0.029	0.006	5.08	0.000	0.018	0.040
age	-0.007	0.001	-7.86	0.000	-0.008	-0.005
agesq1000	0.056	0.009	6.63	0.000	0.040	0.073
syq						
20021	-0.441	0.034	-13.100	0.000	-0.507	-0.375
20022	-0.379	0.038	-10.060	0.000	-0.453	-0.305
20023	-0.375	0.036	-10.480	0.000	-0.446	-0.305
20024	-0.306	0.073	-4.220	0.000	-0.448	-0.164
20031	-0.087	0.056	-1.560	0.118	-0.196	0.022
20032	-0.077	0.037	-2.050	0.040	-0.150	-0.004
20033	-0.025	0.038	-0.670	0.505	-0.100	0.049
20034	-0.035	0.037	-0.950	0.343	-0.108	0.037
20041	0.001	0.031	0.040	0.972	-0.060	0.062
20042	0.095	0.021	4.430	0.000	0.053	0.137
20043	0.121	0.024	5.120	0.000	0.075	0.168
20044	0.124	0.028	4.340	0.000	0.068	0.179
20051	0.137	0.047	2.910	0.004	0.045	0.230
20052	0.204	0.039	5.170	0.000	0.127	0.281
20053	0.164	0.062	2.640	0.008	0.042	0.285
20054	0.202	0.038	5.340	0.000	0.128	0.276
20061	0.159	0.021	7.710	0.000	0.119	0.200
20062	0.163	0.021	7.900	0.000	0.123	0.204
20063	0.160	0.022	7.300	0.000	0.117	0.203
20064	0.071	0.022	3.240	0.001	0.028	0.114
20071	0.162	0.017	9.700	0.000	0.129	0.195
20072	0.124	0.020	6.170	0.000	0.085	0.163
20073	0.074	0.016	4.580	0.000	0.042	0.106
20074	0.002	0.018	0.100	0.919	-0.034	0.038
20081	0.022	0.016	1.360	0.175	-0.010	0.054
20082	-0.005	0.013	-0.380	0.707	-0.031	0.021
20083	-0.050	0.014	-3.690	0.000	-0.077	-0.023
20084	-0.066	0.014	-4.630	0.000	-0.094	-0.038
20091	-0.113	0.014	-8.070	0.000	-0.141	-0.086
20092	-0.116	0.012	-9.800	0.000	-0.139	-0.092
20093	-0.124	0.012	-10.610	0.000	-0.147	-0.101
20094	-0.120	0.012	-9.700	0.000	-0.144	-0.096
20101	-0.121	0.013	-9.030	0.000	-0.147	-0.095
20102	-0.124	0.012	-10.750	0.000	-0.147	-0.102
20103	-0.144	0.012	-11.660	0.000	-0.168	-0.120
20104	-0.171	0.012	-14.070	0.000	-0.194	-0.147
20111	-0.173	0.011	-15.170	0.000	-0.196	-0.151
20112	-0.189	0.011	-17.360	0.000	-0.211	-0.168
20113	-0.190	0.011	-17.040	0.000	-0.212	-0.168
20114	-0.205	0.011	-18.360	0.000	-0.227	-0.183
20121	-0.212	0.011	-19.000	0.000	-0.234	-0.190
20122	-0.176	0.012	-15.180	0.000	-0.199	-0.153
20123	-0.154	0.011	-13.660	0.000	-0.176	-0.132
20124	-0.123	0.012	-10.220	0.000	-0.147	-0.099
20131	-0.090	0.010	-9.480	0.000	-0.109	-0.072
20132	-0.038	0.009	-4.150	0.000	-0.056	-0.020
20133	-0.009	0.009	-1.000	0.317	-0.027	0.009
20134	--- omitted ---					

4.2 Base Model Variations Using Subsamples

As shown in Table 1, many of the research questions can be investigated using variations of the Base Model that use subsamples of the data in place of the full sample. The following sections describe those model sets and include: Location Models, for California and the rest of the United States; Home Type Models, for newly built and existing homes; Age of PV System Models; and Year of Sale Models.

4.2.1 Location Model Results

Our Location Models estimate premiums for either the subset of homes located in California or those located in the rest of the United States; Table 8 shows the results, along with results for the Home Type Models (which are discussed in the next subsection).[28] Also shown in the table, for reference purposes, are the results for the Base Model using the full sample. Results shown for each model include the *pv*size* coefficient, standard error, and *p*-value; the mean non-PV home sale price; the $/W premium and its 95% confidence interval; and estimates for the net and gross costs and PV Value income. Finally, for each model, the table shows the total, PV, and non-PV sample sizes; the adjusted R^2; and the number of block groups represented by the sample. Figure 1 compares the Base and Location Model results, along with the contributory-value estimates, graphically.

The coefficient for the variable of interest for the California subsample is 0.0091, which is highly statistically significant and equates to a $4.21/W premium and a 95% confidence interval of +/- $0.64/W. Not surprisingly, the PV premium is very close to the premium estimated for the full sample, because California PV homes make up 97% of that sample. The PV premium can be compared to the net, gross, and PV Value estimates of $4.16/W, $6.94/W, and $2.95/W, respectively.

For homes outside of California where we have data (in Connecticut, Florida, Massachusetts, Maryland, North Carolina, New York, and Pennsylvania), the PV premium is estimated to be $3.11/W and highly statistically significant (*p*-value < 0.01), but with a 95% confidence interval of $2.33/W. This indicates that, in this broader sample of homes, a premium for PV homes is evident, but the smaller sample of homes outside California does not allow for a very precise estimate of the effect size. The estimated premium is very similar to the net cost estimate for this subset of $3.09/W, and it is not statistically different from the premium estimated for California homes. These findings should give stakeholders outside of California greater confidence that PV adds value to homes in their markets.

---

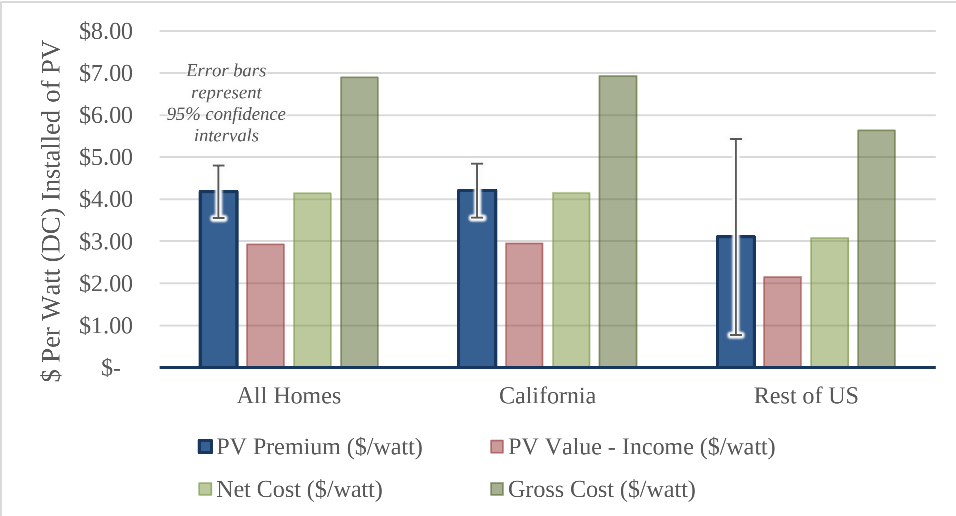
[28] For brevity, only the variable of interest is shown for the remainder of the paper. Results for the controlling variables were similarly signed and leveled across the various models as they are in the Base Model. The full set of results is available upon request.

Table 8: Location and Home Type Model Results[29]

		Location		Home Type	
	All Homes	**California**	**Rest of US**	**New Homes**	**Existing Homes**
PV Premium Estimates					
PV*Size Coefficient	0.0091	0.0091	0.0085	0.0084	0.0094
PV*Size Standard Error	0.0007	0.0007	0.0032	0.0012	0.0008
PV*Size *p* -value	*0.000*	*0.000*	*0.009*	*0.000*	*0.000*
Mean Sale Price Non-PV ($)	$ 456,378	$ 459,366	$ 364,854	$ 422,001	$ 476,124
PV Premium ($/watt)	$ 4.18	$ 4.21	$ 3.11	$ 3.58	$ 4.51
95% CI ($/watt)	$ 0.62	$ 0.64	$ 2.33	$ 1.00	$ 0.71
Contributory Value Estimates					
PV Value - Income ($/watt)	$ 2.93	$ 2.95	$ 2.15	$ 3.04	$ 2.86
Net Cost ($/watt)	$ 4.14	$ 4.16	$ 3.09	$ 3.85	$ 4.29
Gross Cost ($/watt)	$ 6.90	$ 6.94	$ 5.64	$ 7.34	$ 6.65
Model Info					
Total *n*	22,822	22,035	787	7,480	15,342
PV *n*	3,951	3,828	123	1,444	2,507
Non-PV *n*	18,871	18,207	664	6,036	12,835
Adjusted R^2	0.92	0.93	0.88	0.97	0.91
Dependent Variable	lnsp	lnsp	lnsp	lnsp	lnsp
Block Group Fixed Effects *n*	1,830	1,721	109	155	1,766

[29] Here, as in other results tables, the numbers of block groups for subsets of data do not always sum to 1,830. This occurs when the block groups are not mutually exclusive between the subsets, e.g., with new or existing homes.

Figure 1: Base and Location Model Results

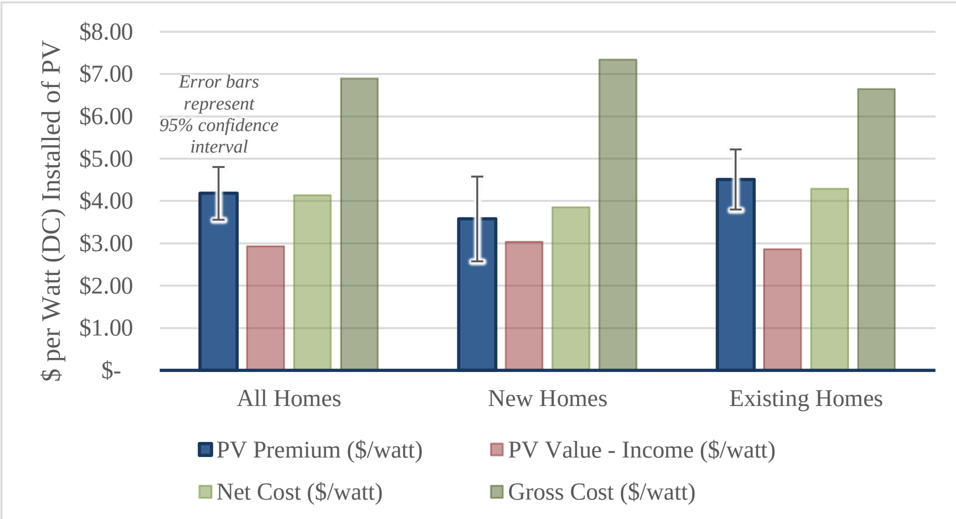


4.2.2 Home Type Model Results

Dividing the data by the type of home, specifically whether the home was newly built or existing at the time of sale, allows examination of the differences between these subgroups. In previous analyses, premiums for existing homes were found to be significantly larger than those for newly built homes, but the sample used was smaller, only for homes in California, only extended through 2009, and included homes with sales prices up to almost $3 million (Hoen et al., 2011; 2013a). The present analysis enables a reexamination of this question by using a sample that is larger, more broadly distributed geographically, has more recent data, and uses homes no more expensive than $900,000.

The results from the Home Type Models that used the new and existing home subsamples are shown in Table 8 and Figure 2. New homes have a premium of $3.58/W, while existing homes have a premium of $4.51/W, a difference of approximately $1/W. Both estimates are highly statistically significant (p-values < 0.001) by themselves, but they are not statistically different from each other (difference in coefficients = 0.001, p-value = 0.46; not shown in table). Therefore, we are unable to uncover a difference in premiums between those subgroups with the larger, more geographically diverse, and more recent dataset. Nonetheless, the differences between these two sets of estimates mimic the different net costs, which are higher for existing homes than for newly built homes.

Figure 2: Home Type Model Results



4.2.3 Age of PV System Model Results

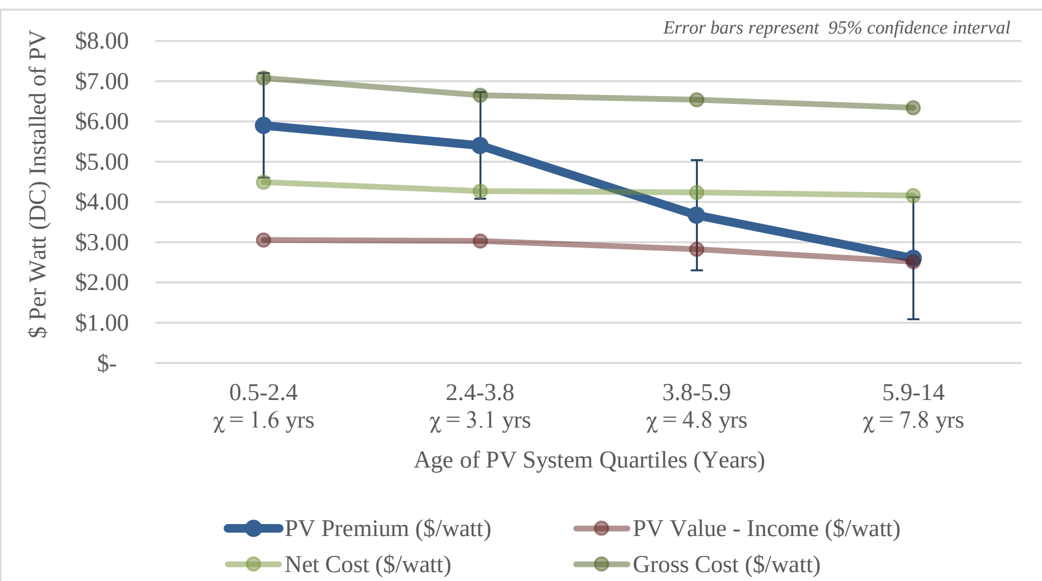
Dividing the full sample into subsamples consisting of four quartiles based on PV system age (0.5–2.4 years, 2.4–3.8 years, 3.8–5.9 years, and 5.9–14 years) allows us to explore if the market accounts for PV system age when valuing PV systems. For this set of quartiles, only existing homes are used, because all newly built homes have PV systems that are also new. Table 9 contains the results for the full set of existing homes and the four other quartile models. Each of the four quartile models uses a different set of PV homes and a set of non-mutually-exclusive, CEM-matched non-PV homes, to which the PV homes are compared.[30] Figure 3 shows the Age of PV System Model results, along with the contributory-value estimates, graphically.

[30] As described above, because the characteristics on which the PV homes are matched to the non-PV homes are exclusive of PV system age, the set of non-PV homes (and the block groups in which they are located) are not mutually exclusive across the models. However, the same rules apply to these subsets in that, for each block group that contains a PV home, at least one matched non-PV home is present.

Table 9: Age of PV System Model Results

		Age of PV System Groups			
	Existing Homes	**0.5-2.4**	**2.4-3.8**	**3.8-5.9**	**5.9-14**
PV Premium Estimates					
PV*Size Coefficient	0.0094	0.0123	0.0113	0.0076	0.0055
PV*Size Standard Error	0.0008	0.0014	0.0014	0.0015	0.0016
PV*Size *p*-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.001*
Mean Sale Price Non-PV ($)	$ 476,124	$ 477,737	$ 474,560	$ 478,634	$ 474,476
PV Premium ($/watt)	$ 4.51	$ 5.90	$ 5.40	$ 3.67	$ 2.60
95% CI ($/watt)	$ 0.71	$ 1.30	$ 1.33	$ 1.37	$ 1.51
Contributory Value Estimates					
PV Value - Income ($/watt)	$ 2.86	$ 3.06	$ 3.03	$ 2.83	$ 2.52
Net Cost ($/watt)	$ 4.29	$ 4.49	$ 4.27	$ 4.24	$ 4.16
Gross Cost ($/watt)	$ 6.65	$ 7.08	$ 6.65	$ 6.54	$ 6.34
Model Info					
Total *n*	15,342	4,398	3,865	4,100	3,607
PV *n*	2,507	633	613	635	626
Non-PV *n*	12,835	3,765	3,252	3,465	2,981
Adjusted R^2	0.91	0.93	0.93	0.92	0.90
Dependent Variable	lnsp	lnsp	lnsp	lnsp	lnsp
Block Group Fixed Effects *n*	1,766	574	504	509	540
Mean PV System Age (years)	4.3	1.6	3.1	4.8	7.8

Figure 3: Age of PV System Model Results



The coefficients for each progressively older subset of PV systems are monotonically ordered, going from 0.0123 for the systems 0.5–2.4 years old to 0.0055 for systems 5.9–14 years old. These translate into premiums of $5.90/W for the newest systems and $2.60/W for the oldest systems, with relatively stable 95% confidence intervals of approximately $1.40/W and somewhat decreasing cost and income estimates.[31] This premium reduction of almost 60% indicates that the market quickly depreciates PV systems in their first 10 years at a rate exceeding an average rate of PV efficiency losses, e.g., 0.5%/year (Dobos, 2014) and also exceeding the depreciation expected were straight-line depreciation applied over the asset's life; this might indicate functional obsolescence setting in. Because the mean age for the oldest quartile (5.9–14 years) is only 7.8 years (Table 9)**Error! Reference source not found.**, however, we cannot describe PV system values as they age into their second decade. Although not shown here, additional models were estimated with additional older age groups (e.g., 10–14 years), but the confidence intervals around those estimates increased such that the results were not any more revealing than what is presented here. In none of the models, however, did we find an estimate close to zero. This seems to indicate that, as systems age, their value flattens out, but additional analysis in future years is needed to understand this trend better.[32]

Finally, it appears that the premiums, as systems age, start well above what would be predicted by the net cost estimates for young systems and then fall well below what would be predicted by the net cost estimates for older systems. This is an artifact of how the net cost estimates are calculated. As discussed in Section 3.2 the cost estimates are prepared without any depreciation and therefore are estimates of a new system. Of course new systems likely would not have the same value as otherwise identical older systems, but knowing the correct amount of depreciation to apply to these estimates is beyond the scope of this work.

4.2.4 Year of Sale Model Results

Because the dataset spans the period from 2002 through 2013, we can examine how premiums change over time. This is especially interesting given that, in the same period, the costs for PV modules dropped (Barbose et al., 2013) and housing market prices saw a rapid rise, fall, and recovery. We break the data into four subsamples roughly consistent with these broad changes (2002–2007, 2008–2009, 2010–2011, and 2012–2013) and estimate the Base Model specification for each subsample.

Results from these models are contained in Table 10 and Figure 4. The model results for the full dataset are also contained in Table 10 for reference. In each model, the coefficient of the variable of interest, *pv*size*, is highly statistically significant (*p*-value ≤ 0.001), with relatively stable standard errors ranging from 0.002 to 0.001, or a tenth of a percent. Despite varying mean non-PV homes prices, which range from $512,170 to $440,495, premiums are relatively stable, ranging from $3.41/W to $4.54/W, with none being statistically different from each other over the various periods.

---

[31] Although not shown here, the average size of PV systems was very similar in all four age bins, at approximately 4.2 kW. We hypothesize that this larger premium for nearly new systems is related to additional nearly new features installed coincidently or the homeowner not fully taking advantage of tax incentives if they had planned on selling the home soon after the installation.

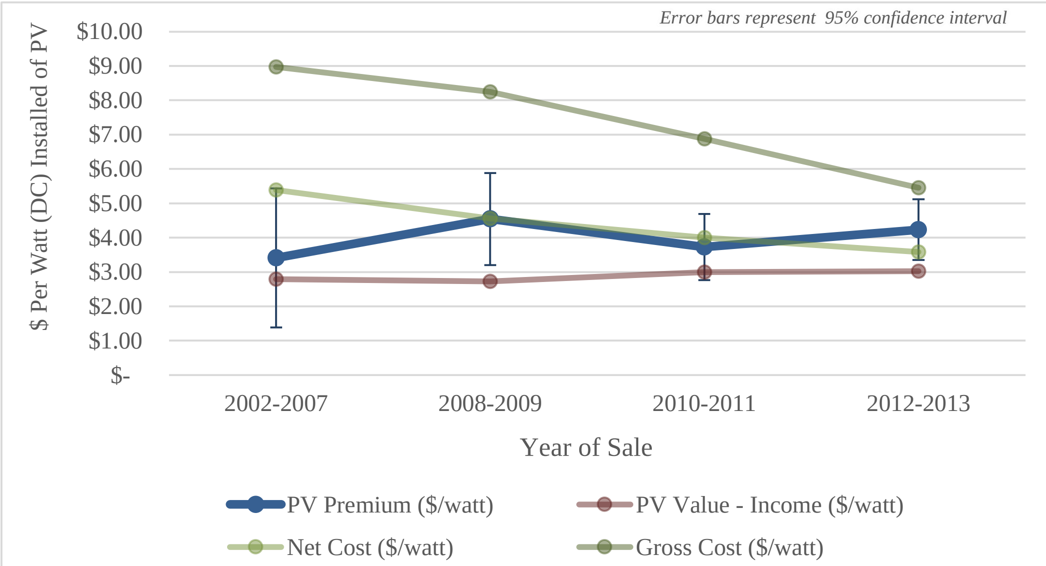
[32] Additionally, we calculated a linear estimate of age of PV interacted with PV system size, which was, not surprisingly, negative and highly statistically significant. Although this reaffirms that increasing age of PV systems is highly correlated with lower premiums, by its very nature it implies that PV systems lose 100% of their value at some point in time. This was calculated to be about 13 years, but it is at the end of our dataset and is not borne out in other tests (e.g., bins shown above, polynomial interactions, and additional binning for older systems). Therefore, we conclude that older systems are of *lower* value, but not of no value, at least given the age distribution of 0 to 14 years contained in the sample.

During this period, we see mean gross costs descend from a high of $8.97/W in 2002–2007 to a low of $5.45/W in 2012–2013. Net costs fall much less between these two periods, from $5.39/W to $3.58/W, while PV Value income estimates remain near, or slightly below, $3/W. Despite falling gross costs and shifts in the overall housing market, premiums remain fairly flat and not statistically different from the net costs in all periods and from the PV Value income estimates in two out of four periods. Clearly home buyers have been willing to pay a reasonably consistent premium for PV despite dramatic changes in both the PV and housing markets. The results also suggest that net cost is a more significant price signal than gross cost.

Table 10: Year of Sale Model Results

		Year of Sale Groups			
	All Homes	**2002-2007**	**2008-2009**	**2010-2011**	**2012-2013**
PV Premium Estimates					
PV*Size Coefficient	0.0091	0.0066	0.0103	0.0083	0.0093
PV*Size Standard Error	0.0007	0.0020	0.0016	0.0011	0.0010
PV*Size *p*-value	*0.000*	*0.001*	*0.000*	*0.000*	*0.000*
Mean Sale Price Non-PV ($)	$ 456,378	$ 512,170	$ 440,495	$ 448,976	$ 453,988
PV Premium ($/watt)	$ 4.18	$ 3.41	$ 4.54	$ 3.73	$ 4.23
95% CI ($/watt)	$ 0.62	$ 2.03	$ 1.34	$ 0.97	$ 0.88
Contributory Value Estimates					
PV Value - Income ($/watt)	$ 2.93	$ 2.79	$ 2.73	$ 3.00	$ 3.02
Net Cost ($/watt)	$ 4.14	$ 5.39	$ 4.56	$ 4.00	$ 3.58
Gross Cost ($/watt)	$ 6.90	$ 8.97	$ 8.25	$ 6.88	$ 5.45
Model Info					
Total *n*	22,822	2,368	3,895	7,238	9,321
PV *n*	3,951	464	882	1,146	1,459
Non-PV *n*	18,871	1,904	3,013	6,092	7,862
Adjusted R^2	0.92	0.96	0.96	0.95	0.91
Dependent Variable	lnsp	lnsp	lnsp	lnsp	lnsp
Block Group Fixed Effects *n*	1,830	259	313	630	1,022

Figure 4: Year of Sale Model Results



4.3 Robustness Models

The various models estimated above, which mostly are based on the Base Model and subsets of the data, compare PV home prices to non-PV home prices. Here we estimate two Robustness Models, which allow us to examine the robustness of the results under alternative specifications: the PV Only Model and the Repeat Sales Model. The PV Only Model compares selling prices of only PV homes, while the Repeat Sales Model examines the selling prices of the same home for homes sold once before the PV system was installed and again after it was installed, as described by Equation (2). These models use both different sets or subsets of the data and different specifications of the model, which allows them to control for possible specification biases in the Base Model. They, therefore, serve as valuable comparisons to and, potentially, validations of the Base Model results.

4.3.1 PV Only Model

Results for the PV Only Model are shown in **Error! Reference source not found.**. The coefficient for *pv*size* is effectively identical to that estimated for the Base Model with the full dataset, and it is highly statistically significant (p-value $\leq$ 0.001). The fact that the coefficient is identical to the Base Model coefficient is remarkable given that it is derived from a model that uses county fixed effects, rather than the more geographically precise block group fixed effect used in the Base Model. The estimated premium is $4.37/W, although the 95% confidence interval is considerably larger at $2.62/W vs. the Base Model's $0.62/W, indicating considerably less precision in the PV Only Model estimate.

4.3.2 Repeat PV Home Model

Results from the Repeat PV Home Model are also shown in **Error! Reference source not found.**. The coefficient for *pv*size* is very similar to that estimated for the Base Model with the full dataset, but it is not statistically significant (p-value = 0.113). The estimated premium is $4.60/W with a 95% confidence interval at $5.69/W, which is considerably larger than those for the Base and PV Only Models.

4.3.3 Summary of Robustness Checks

Because of the large margins of error, we cannot say the three estimates are statistically different from each other. Despite this, none of the results appear markedly different from that estimated using the Base

Model where PV homes are compared to non-PV homes. When comparing PV homes to other PV homes, as in the PV Only Model, or the same PV home to itself over multiple transactions, as in the Repeat PV Home Model, we find little evidence to support the claim that the Base Model PV premium estimate is biased. Therefore, there appears to be no evidence that the PV estimate also contains the effects of other omitted features such as EE upgrades.

Table 11: Year of Sale Model Results

PV Premium Estimates	**All Homes**	**PV Only**	**Repeat**
PV*Size Coefficient	0.0091	0.0092	0.0087
PV*Size Standard Error	0.0007	0.0028	0.0055
PV*Size *p* -value	*0.000*	*0.001*	*0.113*
Mean Sale Price Non-PV ($)	$ 456,377	$ 474,529	$ 528,368
PV Premium ($/watt)	$ 4.18	$ 4.37	$ 4.60
95% CI ($/watt)	$ 0.62	$ 2.62	$ 5.69
Contributory Value Estimates			
PV Value - Income ($/watt)	$ 2.93	$ 2.93	$ 2.15
Net Cost ($/watt)	$ 4.14	$ 4.14	$ 3.09
Gross Cost ($/watt)	$ 6.90	$ 6.91	$ 5.64
Model Info			
Total *n*	22,822	3,915	1,698
PV *n*	3,951	3,915	849
Non-PV *n*	18,871	-	849
Adjusted R^2	0.92	0.68	0.23
Dependent Variable	lnsp	lnsp	lnsp
Fixed Effects *n*	1,830	65	n/a

5. Conclusion

As PV systems become an increasingly common feature of U.S. homes, the ability to value homes with these systems appropriately will become increasingly important. Our study fills important gaps in the PV-home-valuation literature by more than doubling the number of PV home sales previously analyzed, examining transactions in eight different states, and spanning the years 2002–2013. We find home buyers are consistently willing to pay PV home premiums; average premiums equate to approximately $4/W or $15,000 for an average-sized 3.6-kW PV system. We find statistically similar results for new and existing home types and PV homes that sold both inside and outside of California. We find premiums decrease dramatically as PV systems age, dropping almost 60% of their value in the first decade of their expected 25-year life. Finally we find relatively consistent premiums across the 2002–2013 sample period, encompassing the recent housing boom, bust, and recovery.

Our study also compares calculated premiums with contributory-value income, gross cost, and net cost estimates. Despite the large drop in gross costs over the sample period, we see relatively flat PV premiums, indicating that the gross cost is likely not a strong price signal. In contrast, net cost estimates seem to be generally consistent with market value premiums, likely indicating their relevance to buyers and sellers. PV Value income estimates—which for this study use the default average retail rates—are consistently lower than the calculated market premiums. This indicates that a higher retail rate, which reflects avoided costs of not being in that tier after the PV system is installed, would be more appropriate for that portion of the sample.[33]

We recommend a number of areas for future study. This study focuses only on homes with host-owned PV systems. Future analysis should focus on leased systems, because they are a growing portion of the PV home market and have not been studied. In addition, our data are not robust to systems in their second decade, and therefore such older systems should be the focus of future study. Further, although this work allows for a robust analysis of average system premiums across the full dataset, and subsets of the data, the results are not necessarily applicable to individual markets and states that might have unique characteristics. Therefore, any market-specific ("small scale") analysis, especially one that employs appraisers and other valuers in those local markets, would be beneficial. Similarly, collecting and analyzing more data in a wide variety of states individually would be useful. Additionally, because premium differences related to the availability of PV homes are unclear, investigating both buyer's markets (with many PV homes available) and seller's markets (with few PV homes available) would add clarity to PV home valuation. Finally, very large PV systems and systems on commercial properties were not represented in our data; both could have unique valuation characteristics and are thus areas for further study.

[33] For example, for California customers where tiered rates are common, a weighted rate based on tiers and the usage within each tier for particular PV homes might result in a more appropriate estimated value.

6. References

Adomatis, S. and Hoen, B. (2016) An Analysis of Solar Home Paired Sales across Six States. *The Appraisal Journal*. 84(1): 27-42.

Adomatis, S. K. (2014) Residential Green Valuation Tools. Appraisal Institute. Chicago, IL. 191 pages. ISBN 978-1-935328-52-0.

Barbose, G., Darghouth, N., Weaver, S. and Wiser, R. (2013) Tracking the Sun Vi: An Historical Summary of the Installed Price of Photovoltaics in the United States from 1998 to 2012. Lawrence Berkeley National Laboratory. Berkeley, CA. July 2013. 70 pages.

Barbose, G., Weaver, S. and Darghouth, N. (2014) Tracking the Sun Vii: An Historical Summary of the Installed Price of Photovoltaics in the United States from 1998 to 2013. Lawrence Berkeley National Laboratory. Berkeley, CA. September 2014. 66 pages.

California Public Utilities Commission (CPUC) (2010) CPUC California Solar Initiative: 2009 Impact Evaluation. Final Report. Prepared by: Itron and KEMA. Prepared for California Public Utilities Commission, Energy Division. June 2010. 632 pages.

California Public Utilities Commission (CPUC) (2013) California Net Energy Metering Ratepayer Impacts Evaluation. Prepared by: Energy and Environmental Economics Inc. Prepared for CPUC, Energy Division. October 28, 2013. 127 pages.

Dakin, W., Springer, D. and Kelly, B. (2008) Case Study: The Effectiveness of Zero Energy Home Strategies in the Marketplace. Presented at ACEEE Summer Study on Energy Efficiency in Buildings, Pacific Grove, California. August 17–22, 2008.

Dastrup, S. R., Graff Zivin, J., Costa, D. L. and Kahn, M. E. (2012) Understanding the Solar Home Price Premium: Electricity Generation and “Green” Social Status. *European Economic Review*. 56(5): 961-973.

Desmarais, L. (2013) The Impact of Photovoltaic Systems on Market Value and Marketability: A Case Study of 30 Single- Family Homes in the North and Northwest Denver Metro Area. Prepared for Colorado Energy Office. May 2013. 319 pages.

Dobos, A. P. (2014) Pvwatts Version 5 Manual. National Renewable Energy Laboratory (NREL). Golden, CO. September 2014. 20 pages. NREL/TP-6A20-62641.

Fannie Mae (2016) Selling Guide: Fannie Mae Single Family. Washington, DC. August 30, 2016. 1385 pages.

Farhar, B. and Coburn, T. (2008) A New Market Paradigm for Zero-Energy Homes: A Comparative Case Study. *Environment: Science and Policy for Sustainable Development*. 50(1): 18-32.

Federal Housing Authority (FHA) (2015) FHA Single Family Housing Policy Handbook (Handbook 4000.1). 559 pages. March 18, 2015.

Freeman, A. M. (1979) Hedonic Prices, Property Values and Measuring Environmental Benefits: A Survey of the Issues. *Scandinavian Journal of Economics*. 81(2): 154-173.

Hee, C. A., Wedding, C. and Urlaub, I. (2013) Motivations and Behaviors of Solar PV and Geothermal System Owners in North Carolina. Prepared for North Carolina Sustainable Energy Association, Raleigh, NC. December 17, 2013. 18 pages.

Hoen, B., Adomatis, S., Jackson, T., Graff-Zivin, J., Thayer, M., Klise, G. T. and Wiser, R. (2015) Selling into the Sun: Price Premium Analysis of a Multi-State Dataset of Solar Homes. Lawrence Berkeley National Laboratory. Berkeley, CA. January 19, 2015. 33 pages. LBNL-6942E.

Hoen, B., Cappers, P., Wiser, R. and Thayer, M. (2011) An Analysis of the Effects of Photovoltaic Energy Systems on Residential Selling Prices in California. Lawrence Berkeley National Laboratory. Berkeley, CA. April, 2011. 46 pages. LBNL-4476E.

Hoen, B., Cappers, P., Wiser, R. and Thayer, M. (2013a) Residential Photovoltaic Energy Systems in California: The Effect on Home Sales Prices. *Contemporary Economic Policy*. 31(4): 708-718.

Hoen, B., Klise, G. T., Graff-Zivin, J., Thayer, M. and Wiser, R. (2013b) Exploring California PV Home Premiums. Lawrence Berkeley National Laboratory. Berkeley, CA. December 2013. 41 pages. LBNL-6484E.

Johnson, J. L. and Klise, G. T. (2012) PV Value ® - User Manual V. 1.0. Prepared for Sandia National Laboratory, Albuquerque, NM. January 31, 2012. 22 pages. SAND2012-0682P.

King, G., Blackwell, M., Iacus, S. and Porro, G. (2010) Cem: Coarsened Exact Matching in Stata. *Stata Journal.* 9(4): 524-546.

Klise, G. T., Johnson, J. L. and Adomatis, S. A. (2013) Valuation of Solar Photovoltaic Systems Using a Discounted Cash Flow Approach. *Appraisal Journal.* Fall 2013: 314-329.

Langheim, R., Arreola, G. and Reese, C. (2014) Energy Efficiency Motivations and Actions of California Solar Homeowners. Presented at ACEEE 2014 Summer Study on Energy Efficiency in Buildings, Pacific Grove, CA. August 17-22, 2014.

Rosen, S. (1974) Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition. *Journal of Political Economy.* 82(1): 34-55.

Sirmans, G. S., Lynn, M., Macpherson, D. A. and Zietz, E. N. (2005) The Value of Housing Characteristics: A Meta Analysis. Presented at Mid Year Meeting of the American Real Estate and Urban Economics Association. May 2005.

Solar Energy Industries Association (SEIA) and GTM Research (GTM) (2016) U.S. Solar Market Insight Report - Q2 2016. GTM Research (GTM) in Boston MA. Prepared for Solar Energy Industries Association (SEIA), Washington, DC.

SunPower (2008) New Homes with Sunpower Solar Systems Are Bright Spot in Market. Ryness Corporation Report. June 24, 2008. [Press Release].

U.S. Department of Housing and Urban Development (HUD) (2016) FHA Single Family Housing Policy Handbook (Handbook 4000.1). 1014 pages. June 30, 2016.

United States Department of Energy (US DOE) (2012) Sunshot Vision Study. Washington, DC. February, 2012. 320 pages. DOE/GO-102012-3037.

Watkins, T. (2011) Market-Based Investigation of Residential Solar Installation Values in Oregon. Watkins & Associates. Prepared for Energy Trust of Oregon, Portland, OR. September, 2011. 15 pages.